Automatic Calibration of Large Traffic Models

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August 27^{th}, 2015

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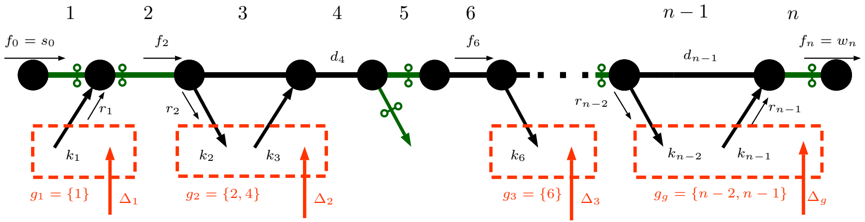
Introduction

and motivation of this work

- Calibrate large traffic models input:
  - Constants of the scenario
  - Source and sink flows depending on day of week & moment of year
- for the output to match:
  - Congestion
  - VMT and VHT
  - Credible ramp flows
- Goal: model accurately a usual traffic situation to make predictions.

Setup

Freeway and traffic model, data, notation



$M = [\![1, n]\!]$	Mainline link indexes	$(f_i)_{i\in M}$	Mainline links exit flows
$R \subset M$	Ramp link indexes	$(d_i)_{i\in M}$	Mainline links densities
$T \subset M$	Monitored mainline links	$(r_i)_{i\in R}$	Ramps exit flows
$K \subset R$	Non-Monitored ramps	$\{\bar{f}_0; (\bar{r}_i)_{i\in R}\}$	Flows inputted to the model
$G = (g_i)_{i\in[\![1,\gamma]\!]}$	Knob group indexes	$(\widetilde{f_i})_{i\in T}$	Measured mainline exit flows
$\vec{k} = (k_{i_1}, k_{i_2} ..., k_{i_\kappa})$	Knobs value vector	$(\widetilde{d_i})_{i\in T}$	Measured mainline densities
$\sigma = (\sigma_{i_1}, \sigma_{i_2} ..., \sigma_{i_\kappa})$	on/off-ramp indicator	$(\widetilde{r_i})_{i\in(R\setminus K)}$	Measured ramps exit flows

Constraints

Physical Boundaries

Let $(t_i(t))_{i \in K}$ the templates:

$$m_i = \frac{[Capacity\ \ of\ \ ramp\ \ associated\ \ to\ \ k_i]}{\max_t t_i(t)}$$

$$\forall i \in K, \qquad 0 \leq k_i \leq m_i \qquad \Leftrightarrow \qquad \vec{k} \in \mathscr{B}$$

Each ramp is closely monitored by mainline sensors.

$$\forall i \in [\![1, \gamma]\!], \qquad \Delta_i = \sum_{t \in \tau} \left[\widetilde{f}_{\beta_i}(t) - \widetilde{f}_{\eta_i}(t) + \sum_{j \in (R \backslash K) \cap S_i} \sigma_j . \widetilde{r}_j(t) \right]$$

$$\cdots$$

$$\cdots$$

$$\cdots$$

$$\Leftrightarrow \qquad \Delta_i = -\sum_{j \in g_i} \sigma_j . k_j . \Theta$$

Constraints

Loosening the constraints: uncertainty

- U^{mul}, U^{add} and U^{global}

- $\forall i \in [\![1, \gamma]\!]$, let the most permissive flow demands:

$$\Delta_i^- = \max\{|\Delta_i| - U^{add}; |\Delta_i|.(1 - U^{mul})\}$$
$$\Delta_i^+ = \min\{|\Delta_i| + U^{add}; |\Delta_i|.(1 + U^{mul})\}$$

- Loosened constraints:

$$\forall i \in [\![1, \gamma]\!],\ \Delta_i^- \leq |\sum_{j \in g_i} \sigma_j.k_j.\Theta| \leq \Delta_i^+$$

Performance and error calculation

Vehicles Hour Traveled (VHT)

- Value computation from model output and data :

$$TVH = \sum_{l \in M} \sum_{t \in [0, \frac{24h}{dt}]} d_l^{(p)}(t) * \frac{dt}{1\ hour}$$

- Relative difference : $\tau_p(TVH) = 100 * \frac{TVH^{BeATS}(p) - TVH^{PeMS}(p)}{TVH^{PeMS}(p)}$

Performance and error calculation

Vehicles Mile Traveled (VMT)

- Value computation from BeATS output and PeMS:

$$TVM(p) = \sum_{l \in M} \sum_{t} f_l^{(p)}(t) * length(l)$$

- $\forall i \in L, f_i(midnight) \approx 0 \Rightarrow$ TVM can be computed before BeATS:
  Let $TVM^{ref} = TVM((1, ..., 1))$ outputed by BeATS

$$TVM^{a\ priori}(k_p) = TVM^{ref} + \sum_{i \in K} \left[\sigma_i . T_i . k_i . \sum_{j \in M, j > i} length(j) \right]$$

$\rightarrow$ Same project & penalize as KD, within I^{global} :

minimize $\left\| k_p - \underline{k_p} \right\|_2$

s.t.

$TVM^{PeMS}.(1 - I^{global}) < TVM^{a\ priori}(k_p) < TVM^{PeMS}.(1 + I^{global})$

$k_p \in [k^{naMin}, k^{naMax}]$

- Relative difference : $\tau_p(TVM) = 100 * \frac{TVM^{BeATS}(p) - TVM^{PeMS}(p)}{TVM^{PeMS}(p)}$

Performance and error calculation

Congestion Pattern matching (CP)

- Principle : match the congested links and times into a box estimated from PeMS contour plot
- Error computation from BeATS output:
  - A congestion treshold is defined for each mainline link :

$$\frac{Link \;\; capacity}{Link \;\; freeflow \;\; speed} + \delta$$

  - The number of pixels of the contour plot that are in the wrong state is the error:

$$CP(p) = \sum_{t \in \frac{24h}{dt}} \sum_{l \in L} \mathbb{1}_{wrong \;\; congestion \;\; state \;\; links}$$

- Relative difference : $\tau_p(CP) = 100 * \frac{CP(p)}{Total \;\; area \;\; of \;\; the \;\; boxes}$

Problem Formulation

Optimization problem statement

- qsd

Numerical method

Requirements

- Continuous search space: here, $\mathcal{S}$ =12-D hypercube
- Function to minimize : mix of correlated and uncorrelated functions with non-differentiable congestion effects

$\rightarrow$ Continuous black-box imputation problem

Numerical method

Covariance Matrix Adaptation - Evolution Strategy (CMA-ES)

- Most powerful evolutionary algorithms for single-objective real-valued optimization (very used)
- "Designed for difficult non-linear non-convex black-box optimisation problems in continuous domain"
- "Typically applied to unconstrained or bounded constraint optimization problems, and search space dimensions between three and a hundred"
- Does not presume existence of approximate gradients : feasible on our non-smooth problem
- *Adaptive* algorithm : almost no parameter tuning $\rightarrow$ suitable to be used on several different freeways and days.
- Time does not matter for this initial study : not the fastest ES but excellent solution quality
- Principle : 12*12 covariance matrix adapts the stochastic sampling direction and step size on-the-go

Numerical method

Constraints implementation (1)

For the single-knob groups, we can refine the knob boundaries using these two uncertainties as a limit:

$$k_i^{min} = max(\{min(\{\alpha.k_i^*; k_i^* - \frac{I^{local}}{\sum_t t_i(t)}\}); 0\})$$

$$k_i^{max} = min(\{max(\{\beta.k_i^*; k_i^* + \frac{I^{local}}{\sum_t t_i(t))}\}); \mu_i\})$$

Repairing : Here, we project the knobs of the group on a space delimited by the two "tolerance hyperplans" for Δ_k:

Let $\overline{k_p}$ the knobs vector to be evaluated at iteration p before projection
Let $J = \{j, card(g_j > 1)\}$ and $\forall i \in K$, $T_i = \sum_t t_i(t)$

minimize $\left\| k_p - \overline{k_p} \right\|_2$
s.t.
$\forall j \in J \quad min(\{\alpha.\Delta_j; \Delta_j - I^{local}\}) < \sum_{i \in g_j} \sigma_i.k_i.T_i < max(\{\beta.\Delta_j; \Delta_j + I^{local}\})$
$k \in [k^{naMin}, k^{naMax}]$

Experiment settings

Data

- qsd

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Experiment settings

Implementation of congestion pattern

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Experiment results

General observations

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Experiment results

Typical execution

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Experiment results

Effect of U^{mul}

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Experiment results

Effect of U^{add}

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Experiment results

Effects of σ

- qsd

Experiment results

Effects of λ

- qsd

Further work

Next steps and ideas

- qsd